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Exploiting the monthly data flow in structural forecasting[☆]

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Abstract

The paper develops a framework which allows to combine the tools provided by structural models for economic interpretation and policy analysis with those of reduced form models designed for now-casting. We show how to map a quarterly dynamic stochastic general equilibrium (DSGE) model into a higher frequency (monthly) version that maintains the same economic restrictions. Moreover we show how to augment the monthly DSGE with auxiliary data that can enhance the analysis and the predictive accuracy in now-casting and forecasting. Our empirical results show that both the monthly version of the DSGE and the auxiliary variables help in real time for identifying the drivers of the dynamics of the economy.

JEL Classification:C33, C53, E30

Keywords: DSGE models, forecasting, temporal aggregation, mixed frequency data, large datasets

[☆]*The views expressed in this paper are those of the authors, and not those of the Bank of England or its committees.*

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1. Introduction

This paper develops an analytical framework to combine the structural analysis based on dynamic stochastic general equilibrium (DSGE) models with reduced form analysis designed for digesting the real-time flow of data publication. The aim is to obtain early signals on the current state of the economy and read it through the lens of a structural model.

Now-casting with DSGE models raises two challenges. First, these models are typically estimated with quarterly data on a balanced panel. Therefore, even if some of the model's variables are available at a higher frequency, this information is lost. Second, DSGE models are estimated on a set of variables that is more limited than the information set used by markets and policymakers, who can exploit more timely information as it progressively becomes available throughout the quarter according to an asynchronous calendar of data publications. But, as we will show, this information is valuable not only for pure forecasting/now-casting purposes but also for identifying economically meaningful shocks in real time.

An extensive recent now-casting literature, starting with Giannone, Reichlin and Small (2008), has made use of the state-space representation of reduced form statistical models to provide early estimates of the current value of key quarterly variables such as GDP in relation to the data flow. In this approach, given the model parameters, the newly available data, particularly those published earlier than national account quarterly data, help to produce progressively more accurate estimates of the states and therefore of

24 the current quarter value of the data. This is true not only for “hard” data
25 such as industrial production or employment but also for “soft” data such
26 as surveys which are the first to provide information on the current quarter
27 (for a survey see Banbura, Giannone and Reichlin, 2011). We exploit the fact
28 that both the now-casting model of Giannone, Reichlin and Small (2008) and
29 the generic DGSE have a state space form to link the two approaches in a
30 formal way. This involves three elements.

31 First, we derive the monthly dynamics of the model, addressing a classic
32 problem of time aggregation (for an early discussion, see Hansen and Sargent
33 1991). Our contribution here is to provide a method for assessing when a
34 linear or linearised quarterly model has a unique monthly specification with
35 real coefficients and to select the appropriate monthly specification, if there
36 is more than one. Second, we make use of the monthly specification of the
37 model to exploit the infra-quarter data which are available at a monthly
38 frequency. Third, we augment it with data which are typically not included
39 in structural models, because they do not have much relevance at a quarterly
40 frequency, but that are potentially useful because of their timeliness. An
41 obvious example are surveys whose value is only due to their short publication
42 lag and, by the end of the quarter, do not convey any additional information
43 beyond GDP growth itself.

44 The empirical application provided in the paper illustrates the potential
45 use of the method for both policy modeling and academic research. We derive
46 the monthly state-space that coincides, when put on quarterly data, with a

47 variant of the model in Galí, Smets and Wouters (2012) that incorporates
48 financial frictions as in Bernanke, Gertler and Gilchrist (1999) and augment
49 it with auxiliary monthly macro indicators potentially useful for now-casting.
50 We assess the method’s performance in terms of forecast accuracy both on
51 average over the whole evaluation sample, and in the specific episode of the
52 Lehman Bros. crisis. We find that the now-cast and forecast accuracy of the
53 monthly model augmented with the auxiliary variables is comparable to that
54 of the survey of professional forecasters (SPF) and greatly improves over the
55 quarterly model. These results are in line with similar findings for reduced-
56 form models (e.g. Giannone, Reichlin and Small, 2008). But here, crucially,
57 we have a structural model, so we can also exploit the real-time information
58 flow to now-cast unobservables variables that are useful for understanding
59 the economy’s dynamics, such as the output gap or the shocks that drive the
60 model.

61 To exploit further the possibilities that our framework offers for structural
62 analysis, we focus on the Lehman Bros. crisis and we compare the augmented
63 monthly model’s storytelling in real-time to the one we would have obtained
64 conditioning on the now-casts of the SPF, as suggested in Del Negro and
65 Schorfheide (2013). Thanks to the auxiliary information, our model is able to
66 better identify, in real time, the shocks driving the business cycle. Moreover,
67 our approach delivers an interpretation of the auxiliary variables through the
68 lens of the model.

69 The paper is organized as follows. In the first section we illustrate the

70 methodology, in the second the data and the structural model, in the third
71 we provide a forecast evaluation while in the fourth we use the framework
72 for real time structural analysis. Finally we comment the relation of our
73 approach to the related literature and conclude.

74 **2. The methodology**

75 *2.1. From monthly to quarterly specification*

76 In what follows, we show how to obtain the monthly specification of the
77 quarterly DSGE model that has real coefficients and we discuss under which
78 conditions such a monthly model exists and is unique. We then discuss how
79 to link the monthly model with the auxiliary variables for now-casting.

80 We consider structural quarterly models whose log-linearized solution has
81 the form:

$$s_{t_q} = \mathcal{T}_\theta s_{t_q-1} + \mathcal{B}_\theta \varepsilon_{t_q} \quad (1)$$

$$Y_{t_q} = \mathcal{M}_{0,\theta} s_{t_q} + \mathcal{M}_{1,\theta} s_{t_q-1}$$

82 where t_q is time in quarters, $Y_{t_q} = (y_{1,t_q}, \dots, y_{k,t_q})'$ is a set of observable
83 variables which are transformed to be stationary, s_t are the states of the
84 model and ε_t are structural orthonormal shocks. The autoregressive matrix
85 \mathcal{T}_θ , the coefficients \mathcal{B}_θ , $\mathcal{M}_{0,\theta}$ and $\mathcal{M}_{1,\theta}$ are function of the deep, behavioural
86 parameters of the DSGE model, which are collected in the vector θ . $\mathcal{M}_{1,\theta}$
87 accounts for the fact that often a part of the observables are defined in first

88 differences. We consider the model and its parameters as given. The vector
 89 s_t can also include the lags of the state variables and shocks.¹

90 Let us define t_m as the time in months and denote by $Y_{t_m} = (y_{1,t_m}, \dots, y_{k,t_m})'$
 91 the vector of the possibly latent monthly counterparts of the variables that
 92 enter the quarterly model. The latter are transformed so as to correspond
 93 to a quarterly quantity when observed at end of the quarter, i.e. when t_m
 94 corresponds to March, June, September or December (e.g. see Giannone,
 95 Reichlin and Small, 2008).

For example, let y_{i,t_m} be the unemployment rate u_{t_m} and suppose that it
 enters the quarterly model as an average over the quarter, then:

$$y_{i,t_m} = \frac{1}{3}(u_{t_m} + u_{t_m-1} + u_{t_m-2})$$

In accordance with our definition of the monthly variables, we can define the
 vector of monthly states s_{t_m} as a set of latent variables which corresponds to
 its quarterly model-based concept when observed on the last month of each
 quarter. Hence, it follows that our original state equation

$$s_{t_q} = \mathcal{T}_\theta s_{t_q-1} + B_\theta \varepsilon_{t_q}$$

¹The inclusion of the states and their lag in the observation equation is useful to model
 variables that enter the system in difference. An alternative consists in including the
 differences of the states as additional states and setting $\mathcal{M}_{0,\theta} = S_{k,n}$ and $\mathcal{M}_{0,\theta} = 0$,
 where $S_{k,n}$ is a matrix of zeros and ones that just selects the appropriate rows of s_{t_q} . The
 problem with this approach is that it generates more redundant states and this makes
 more difficult to derive the minimal state representation, a step that as we will see is
 particularly important in the proposed procedure.

96 can be rewritten in terms of the monthly latent states as

$$s_{t_m} = \mathcal{T}_\theta s_{t_m-3} + B_\theta \varepsilon_{t_m} \quad (2)$$

97 when t_m corresponds to the last month of a quarter, i.e. when t_m corresponds
98 to March, June, September or December.

99 We assume that the monthly states can be written as

$$s_{t_m} = \mathcal{T}_m s_{t_m-1} + \mathcal{B}_m \varepsilon_{m,t_m} \quad (3)$$

100 and that \mathcal{T}_m is real and stable and ε_{m,t_m} are orthonormal shocks². This
101 implies:

$$s_{t_m} = \mathcal{T}_m^3 s_{t_m-3} + [\mathcal{B}_m \varepsilon_{m,t_m} + \mathcal{T}_m \mathcal{B}_m \varepsilon_{m,t_m-1} + \mathcal{T}_m^2 \mathcal{B}_m \varepsilon_{m,t_m-2}]. \quad (4)$$

102 We are interested in finding a mapping from the quarterly model to the
103 monthly model: the relation between equations (1), or equivalently (2), and
104 (4) imply that the monthly model can be recovered from the following equa-

²If the variables considered are stocks, the formulation (3) implies no approximation, because selecting a lower frequency just means sampling at a different frequency. If instead the variables considered are flows, then our definition of the monthly variables as an average over the quarter implies that we are introducing a non-invertible moving average in the growth rates. Therefore modeling this monthly concept as autoregressive introduces some misspecification. Doz, Giannone and Reichlin, 2012 show the effect of such misspecification is small.

105 tions:

$$\mathcal{T}_m = \mathcal{T}_\theta^{\frac{1}{3}} \quad (5)$$

$$vec(\mathcal{B}_m \mathcal{B}'_m) = (I + \mathcal{T}_m \otimes \mathcal{T}_m + \mathcal{T}_m^2 \otimes \mathcal{T}_m^2)^{-1} vec(\mathcal{B}_\theta \mathcal{B}'_\theta). \quad (6)$$

106 From (5) it is clear that finding such mapping is equivalent to finding the
107 cube root of \mathcal{T}_θ .

If the autoregressive matrix of the transition equation is diagonalizable, *i.e* if there exist a diagonal matrix D and an invertible matrix V such that $\mathcal{T}_\theta = V D V^{-1}$, then the cube root of \mathcal{T}_θ can be obtained as

$$\mathcal{T}_\theta^{\frac{1}{3}} = V D^{\frac{1}{3}} V^{-1},$$

108 where $D^{\frac{1}{3}}$ is a diagonal matrix containing the cube roots of the elements of
109 D . The real elements of D , which are associated with real-valued eigenvectors,
110 have a unique real cube root, which is the only one that gives rise to
111 real values when combined with its associated eigenvector. For the eigenvalues
112 that are complex conjugate instead there are three complex cube roots.
113 These, when combined with their associated eigenvalue, return a real-valued
114 vector. So, effectively, if k is the number of complex conjugate couples of
115 eigenvalues in D , then there will be 3^k real-valued cube roots for \mathcal{T}_θ . To
116 select among these alternative cube roots of \mathcal{T}_θ we proceed as follows. In the
117 case of real eigenvalues, we simply select their real cube root. In the case of

118 complex conjugate couples, we choose the cube root which is characterized
 119 by less oscillatory behaviour, i.e. the cube root with smaller argument.

120 If monthly observations for some variables are available, we can use them
 121 to identify the cube root by choosing the one that maximizes the likelihood of
 122 the data. The cube root selected is generally unique. Indeed, Anderson *et al.*
 123 (2014) have shown that having mixed frequency observation typically implies
 124 identifiability. In our case the two procedures produce the same results.

125 If \mathcal{T}_θ is not diagonalizable, it is possible to obtain the Jordan form³ and to
 126 derive the cube root based on that. An interesting result is that the procedure
 127 described for diagonalizable matrices extends to this situation in most cases
 128 (see Higham, 2008). However there is a caveat that is of particular relevance
 129 for DSGE models. Namely, Higham (2008) proves that there exists no p-th
 130 (so also no cube) root of a matrix that has zero-valued eigenvalues that are
 131 defective, *i.e.* that are multiple but not associated to linearly independent
 132 eigenvectors. In the case of DSGE models, this situation arise mainly, but not

³Any matrix $A \in \mathbb{C}^{n \times n}$ can be expressed in the canonical Jordan form

$$Z^{-1}AZ = J = \text{diag}(J_1, J_2, \dots, J_p),$$

with

$$J_k = J_k(\lambda_k) = \begin{bmatrix} \lambda_k & 1 & & \\ & \lambda_k & \ddots & \\ & & \ddots & 1 \\ & & & \lambda_k \end{bmatrix} \in \mathbb{C}^{m_k \times m_k},$$

where Z is non-singular and $m_1 + m_2 + \dots + m_p = n$ with p the number of blocks. We will denote by s the number of distinct eigenvalues (see, for example, Higham (2008) for further details).

133 exclusively, when there are redundant states. It is hence important to work
 134 on the model to try to reduce it to a minimal state space. When defective
 135 zero-valued eigenvalues appear even in the transition matrix of the minimal
 136 state space (for example because of the choice of observables), then we suggest
 137 considering whether there are ways to render the model diagonalizable.

138 We can obtain $\mathcal{B}_m \mathcal{B}'_m$ as the solution of equation (6). As we are interested
 139 in recovering \mathcal{B}_m , we make the additional assumption that the three monthly
 140 shocks are the same and coincide with the quarterly shock, *i.e.* $\varepsilon_{m,t_m} =$
 141 $\varepsilon_{m,t_m-1} = \varepsilon_{m,t_m-2} = \varepsilon_{t_q}$. Under this assumption, we can obtain \mathcal{B}_m directly
 142 from the following equation:

$$\mathcal{B}_m + \mathcal{T}_m \mathcal{B}_m + \mathcal{T}_m^2 \mathcal{B}_m = \mathcal{B}_q.$$

143 Let us now turn to the equation that links the states to the observables.
 144 We start by analyzing the (not very realistic) case in which all variables are
 145 observable at monthly frequency. The monthly observation equation would
 146 then be:

$$Y_{t_m} = \mathcal{M}_m s_{t_m} \tag{7}$$

where

$$\mathcal{M}_m = (\mathcal{M}_{0,\theta} + 0 \cdot L + 0 \cdot L^2 + \mathcal{M}_{1,\theta} L^3)$$

147 The equations (3) and (7) therefore describe the monthly dynamics that
 148 are compatible with the quarterly model.

149 *2.2. Mixed frequency and jagged edged data*

150 If all the observables of the model were available at a monthly frequency,
 151 we could simply use the monthly model defined by equations (3) and (7) to
 152 immediately incorporate this higher frequency information. However, some
 153 variables - think of GDP, for example - are not available at monthly fre-
 154 quency. So let us assume that the variable in the i -th position of the vector
 155 of observables Y_{t_m} , i.e. y_{i,t_m} , is not available at a monthly frequency, but
 156 only at the quarterly frequency. This means that y_{i,t_m} is a latent variable
 157 when t_m does not correspond to the end of a quarter. Moreover, due to
 158 the unsynchronised data release schedule, data are not available on the same
 159 span (the dataset has jagged edges). The unavailability of some data does
 160 not prevent us from still taking advantage of the monthly information that
 161 is available using a Kalman filter. To do so, we follow Giannone, Reichlin
 162 and Small (2008) and define the following state space model

$$s_{t_m} = \mathcal{T}_m s_{t_m-1} + \mathcal{B}_m \varepsilon_{m,t_m}$$

$$Y_{t_m} = \mathcal{M}_m(L) s_{t_m} + V_{t_m}$$

163 where $V_{t_m} = (v_{1,t_m}, \dots, v_{k,t_m})$ is such that $\text{var}(v_{i,t_m}) = 0$ if y_{i,t_m} is available
 164 and $\text{var}(v_{i,t_m}) = \infty$ otherwise.

165 *2.3. Bridging the model with the additional information*

166 We denote by $X_{t_m} = (x_{1,t}, \dots, x_{n,t})'$ the vector of these auxiliary stationary
 167 monthly variables transformed so as to correspond to quarterly quantities at

168 the end of each quarter, as described above.

169 Let us now turn to how we incorporate the auxiliary monthly variables in
170 the structural model. As a starting point we define the relation between the
171 auxiliary variables X_{t_q} and the model's observable variables at a quarterly
172 frequency:

$$X_{t_q} = \mu + \Lambda Y_{t_q} + e_{t_q} \quad (8)$$

173 where e_{t_q} is orthogonal to the quarterly variables entering the model. We will
174 use this equation to estimate the coefficients Λ and the variance-covariance
175 matrix of the shocks $E(e_{t_q} e_{t_q}') = R$. We use a flat prior on all the parameters,
176 so that the posterior model corresponds to the OLS estimate.

177 Let us now focus on incorporating the auxiliary variables in their monthly
178 form. As stressed above, $X_{t_m} = (x_{1,t}, \dots, x_{n,t})'$ is the vector of these auxiliary
179 stationary monthly variables transformed so as to correspond to quarterly
180 quantities at the end of each quarter. We can relate X_{t_m} to the monthly
181 observables Y_{t_m} using the equivalent of equation (8) for the monthly frequency
182 (the bridge model):

$$X_{t_m} = \mu + \Lambda Y_{t_m} + e_{t_m} \quad (9)$$

183 where $e_{t_m} = (e_{1,t_m}, \dots, e_{k,t_m})$ is such that $\text{var}(e_{i,t_m}) = [R]_{i,i}$ if X_{i,t_m} is available
184 and $\text{var}(e_{i,t_m}) = \infty$ otherwise. In this way we take care of the problem of the
185 jagged edge at the end of the dataset, due to the fact that the data is released
186 in an unsynchronized fashion and that the variables have different publishing

187 lags (e.g. capacity utilization releases refer to the *previous* month's total
188 capacity utilization, while the release of the Philadelphia Business Outlook
189 Survey refers to the *current* month). We will use equation (9) to expand
190 the original state-space derived in Section 2.2. Summing up, the state space
191 takes the form:

$$\begin{aligned}
s_{t_m} &= \mathcal{T}_m s_{t_m-1} + \mathcal{B}_m \varepsilon_{m,t_m} \\
Y_{t_m} &= \mathcal{M}_m(L) s_{t_m} + V_{t_m} \\
X_{t_m} - \mu &= \Lambda Y_{t_m} + e_{t_m}
\end{aligned} \tag{10}$$

192 where V_{t_m} and e_{t_m} are defined above. The state-space form (10) allows us to
193 account for and incorporate all the information about the missing observables
194 contained in the auxiliary variables.

195 The choice of modeling X_{t_m} as solely dependent on the observables Y_{t_m}
196 rather than depending in a more general way from the states s_{t_m} , is motivated
197 by the fact that we want the auxiliary variables to be relevant *only* in real
198 time, but we do not want them to affect the inference about the history of
199 the latent states and shocks. In this way the procedure is minimally invasive
200 with respect to the original quarterly model.

201 **3. Empirical analysis**

202 *3.1. The structural model*

203 We implement the methodology described above on a variant of the
204 medium-scale model presented in Galí, Smets and Wouters (2012; henceforth
205 GSW) that includes financial frictions as in Bernanke, Gertler and Gilchrist
206 (1999). The GSW reformulates the well known Smets-Wouters (2007; hence-
207 forth SW) framework by embedding the theory of unemployment proposed
208 in Galí (2011a,b). The main difference of the GSW with respect to the
209 SW is the explicit introduction of unemployment, and the use of a utility
210 specification that parameterizes wealth effects, along the lines of Jaimovich
211 and Rebelo (2009). We add the financial frictions building on the work of
212 Christiano, Motto and Rostagno (2003), De Graeve (2008) and Del Negro,
213 Hasegawa and Schorfheide (2014). In this set-up, banks collect deposits from
214 households and lend to entrepreneurs, who are hit by idiosyncratic shocks
215 to their net wealth. The entrepreneurs use a mix of these funds and their
216 wealth to acquire physical capital, but because of their idiosyncratic shocks,
217 their revenues may be too low to repay the loans. The banks therefore protect
218 themselves charging a spread over the deposit rate, which will be a function of
219 the entrepreneurs' leverage and riskiness. We present the main log-linearized
220 equations of the model in Appendix A and refer to Galí, Smets and Wouters
221 (2012) for an in depth discussion of the model.

222 The model is estimated on nine data series for the US: per capita GDP
223 growth, per capita consumption growth, per capita investment growth, a

224 measure of real wage inflation based on compensation per employee, the GDP
225 deflator inflation, per capita employment, the policy rate, the unemployment
226 rate and a measure of the spread, namely, the annualized Moody’s Seasoned
227 Baa Corporate Bond Yield spread over the 10-Year Treasury Note Yield
228 at Constant Maturity. The policy rate is the effective Fed Funds rate in
229 the part of the sample when it is not constrained by the zero lower bound.
230 From January 2009 onward, the policy rate corresponds to the shadow rate
231 computed by Wu and Xia (2014), which is intended to capture the effects
232 on the term structure of unconventional policy tools such as large-scale asset
233 purchases and forward guidance.

234 GDP growth, investment growth, wage growth are available at a quarterly
235 frequency only, while nominal consumption growth, employment, unemploy-
236 ment, the policy rate and the spread are available at monthly frequency, at
237 least. The model however is specified and estimated at quarterly frequency:
238 we report the model’s priors in Appendix A, while the model’s posterior dis-
239 tribution is estimated annually at the beginning of each year of the evaluation
240 sample, which goes from 1995 to 2014.

241 The model includes nine structural shocks: risk premium, monetary pol-
242 icy, exogenous spending, investment-specific technology shock, neutral tech-
243 nology, price mark-up, wage mark-up, net worth and exogenous labour supply
244 shocks.⁴ Figure 1 shows the decomposition of GDP growth.

⁴All the shocks are AR(1) bar the monetary policy shock, which is white noise.

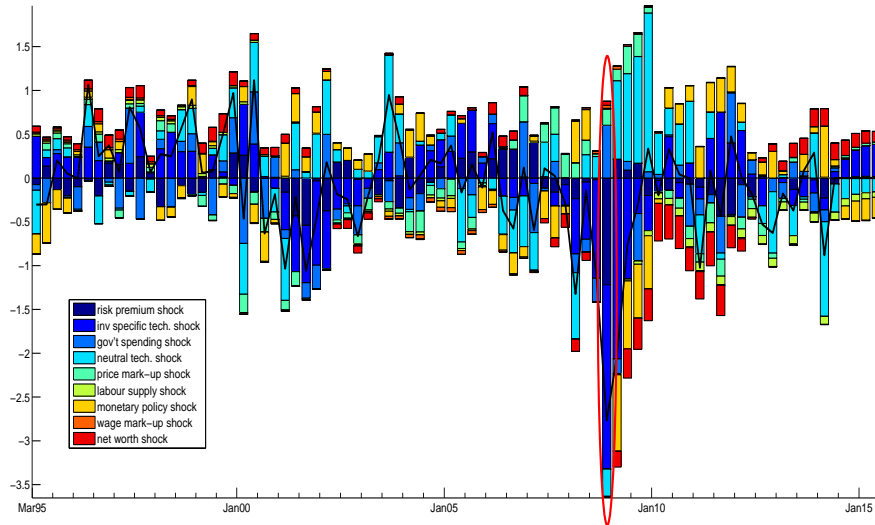


Figure 1: **Shock decomposition of quarterly GDP growth**

Results confirm that over the whole sample the investment specific shock plays a sizeable role (as in Justiniano, Primiceri and Tambalotti, 2010) though the presence of the net worth shock in the model, as in Del Negro, Hasegawa and Schorfheide (2014), reduces its importance. The presence of the labour supply shock in the GSW somewhat reduces the importance of the wage mark-up shocks in the SW first pointed out by in Chari, Kehoe and Mc Grattan (2009).

Interestingly, our model attributes the bulk of the fall in GDP at the end of 2008 (highlighted in red) to three shocks: *i*) the risk premium shock, a perturbation to agents intertemporal Euler equation governing the accumulation of the risk-free asset, which plausibly captured the changes to risk attitudes brought about by the collapse of Lehman Brothers; *ii*) the investment spe-

257 cific technology shock, which also affects the net worth of the entrepreneurs
 258 in the model, and *iii*) the neutral technology shock. Our findings are broadly
 259 consistent with those of Christiano, Eichenbaum and Trabandt (2015), who
 260 analyse the Great Recession through the lens of a state-of-the-art New Key-
 261 nesian model and attribute the bulk of the movements in aggregate real
 262 variables and inflation to a consumption wedge, a financial wedge and the
 263 neutral technology shock.

264 *3.2. The auxiliary variables*

265 We consider a dozen of additional macro and financial variables that are
 266 monitored more closely by professional and institutional forecasters⁵. These
 267 include real indicators (such as industrial production, house starts, total
 268 construction, etc...), price data (CPI, PPI, PCE inflation), financial market
 269 variables (the fed funds rate and the BAA-AAA spread), labour market vari-
 270 ables, credit variables, a measure of uncertainty (Baker, Bloom and Davis
 271 (2015) economic policy uncertainty index) and some national accounts quan-
 272 tities. A full list and description of these series is reported in Table B.4
 273 in Appendix B, which describes a stylised calendar of data releases where
 274 the variables have been grouped in 38 clusters according to their timeliness.
 275 This allows us to relate the changes in the forecast with groups of variables

⁵For a discussion of alternative ways of selecting the auxiliary variables, see Cervena and Schneider (2014), who apply the methodology proposed in the earlier version of this paper (Giannone, Monti and Reichlin, 2010) to a medium-scale DSGE model for Austria and address the issue of variable selection by proposing three different methodologies for the subsample selection.

276 with similar economic content. For example, although the housing sector is
277 not included in the model, we can capture information about it thanks to
278 the auxiliary variables. Similarly, surveys can be very informative, because
279 they give a measure of changes in the private agents' sentiments that is not
280 explicitly modelled in the standard log-linearised DSGE.

281 In the first column of Table B.4 we indicate the progressive number as-
282 sociated to each “vintage” or release cluster, in the second column the data
283 release, in the third the series and in the fourth the date the release refers
284 to, which gives us the information on the publication lag. We can see, for
285 example, that the Philadelphia Fed Survey is the first release referring to the
286 current month m and it is published on the third Thursday of each month.
287 Hard data arrive later. For example, the first release of industrial production
288 regarding this quarter is published in the middle of the second month of the
289 quarter. GDP, released in the last week of the first month of the quarter
290 refers to the previous quarter.

291 Figure 2 reports the portion of the variance of the one-quarter-ahead
292 forecast of the auxiliary variables that is attributed to each of the shocks
293 in the model. Looking at the variance decomposition provides interesting
294 insights on which kind of information the auxiliary variables deliver. Notice
295 that in addition to the structural shocks these variables are also affected by an
296 idiosyncratic shock. The larger the idiosyncratic shock the less informative
297 is a variable about the model dynamics.

298 Let us focus on the three shocks that are driving the fall in GDP in

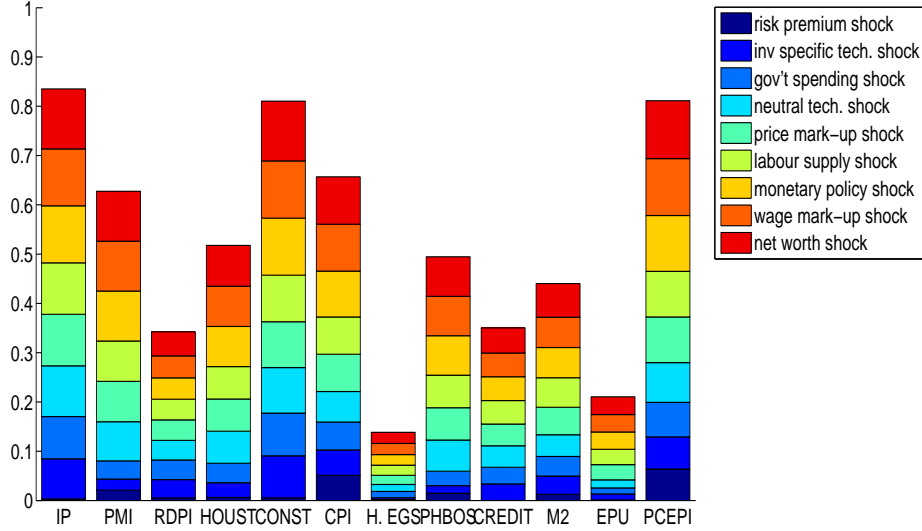


Figure 2: **Forecast error variance decomposition of the auxiliary variables one quarter ahead.**

2008Q4, namely the risk premium shock, the investment specific technology shock and the neutral technology shock. The figures show that the risk premium shock is most relevant for nominal variables (such as CPI inflation and the PCE inflation) and surveys on the real economy such as the PMIs. On the other hand, the variables that are significantly affected by the neutral technology shock are mostly real, like industrial production, housing starts, total construction and the surveys (PHBOS and PMI).

3.3. The derivation of the monthly model

Let us now consider the computation of monthly version of the model. We first verify that \mathcal{T}_θ in (1) can be diagonalized. Indeed it can, so we obtain the matrix D of eigenvalues and the corresponding matrix V of eigenvectors

310 that satisfy $\mathcal{T}_\theta = VDV^{-1}$. We identify the model's real-valued cube root as
311 described in the previous Section and we also verify that it is indeed the one
312 that maximizes the likelihood.

313 We then produce the now-cast with the monthly model with and without
314 auxiliary variables and compare it both to the SPF's forecasts and to the
315 forecast produced with the quarterly model, in which the last data point
316 available is inputted for the higher frequency variables, as is generally done
317 in policy institutions. And we will also obtain real-time estimates of purely
318 model-based concepts like the output gap. As we will show in the next
319 Section, simply taking advantage of all the information available about the
320 observables at a monthly frequency greatly increases the forecasting perfor-
321 mance of the model. Incorporating information from key macro variables
322 that are more timely also helps, especially for GDP growth.

323 4. Forecast Evaluation

324 In this Section we evaluate the forecasting performance of the monthly
325 model augmented by auxiliary variables (M Augmented) and compare it with:
326 the quarterly DSGE model based on the balanced panel (Q balanced), and
327 the monthly model (M model). The forecasts are evaluated at different dates
328 within the quarter in order to assess the effect of timely monthly information
329 on the accuracy of the forecasts. We also benchmark these forecasts against
330 the survey of professional forecasters (SPF) although this is only possible at

331 the middle of the quarter when the such surveys are published⁶.

332 We show both point forecasts and density forecasts, focusing on the evalu-
333 ation sample 1995Q1-2014Q2. Over this sample, the model is estimated once
334 a year using data from 1964 to the year before the one we are evaluating.
335 Due to availability issues we use data from 1982 to estimate the relationship
336 between the auxiliary variables and the model (Λ in system (10)). Because
337 only few of the auxiliary variables we consider are available in real-time from
338 the beginning of the evaluation sample in 1995Q1, we perform the exercise
339 in pseudo-real-time: we use the latest vintage of data, but, at each point of
340 the forecast horizon, we only use the data available at the time.

341 4.1. Point Forecasts

342 In the main text we present now-casts and forecasts of per capita real
343 GDP growth, GDP deflator inflation, unemployment and the output gap.
344 In Appendix we report further results for consumption growth, the policy
345 rate, unemployment and GDP deflator inflation. The figures and tables in
346 this section report the root mean square forecast error (RMSFE) for the
347 different models. In order to align the SPF's and the models' information
348 sets as closely as possible we display it only from cluster 18 to cluster 20, *i.e.*
349 around the beginning of the second month of the quarter when the SPF's
350 forecasts are published.

⁶Where necessary, the SPFs forecast are adjusted by the same population growth index used in the model, in order to align them as much as possible with the models' forecasts, which are in per capita terms.

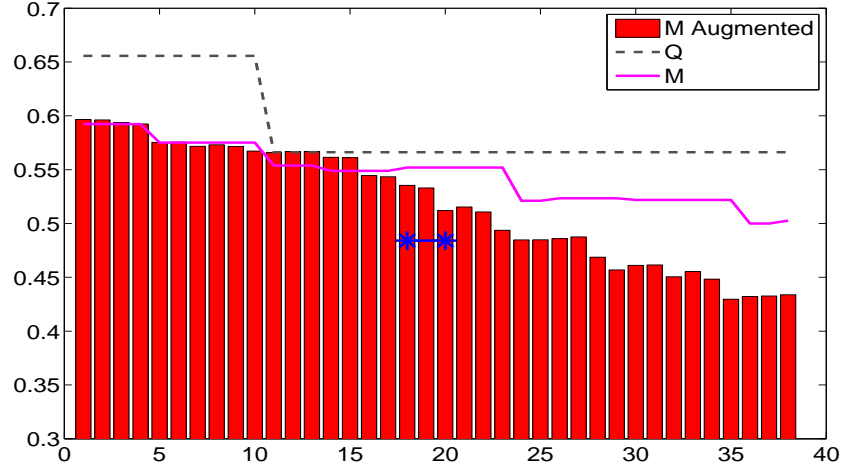


Figure 3: RMSFE of GDP growth now-casts throughout the quarter for the quarterly model (Q, the dashed line), the monthly model (M, the purple line) and the monthly model augmented with the auxiliary information (M Augmented, the red bars). We also report the SPF now-casts, in blue with an asterisk marker.

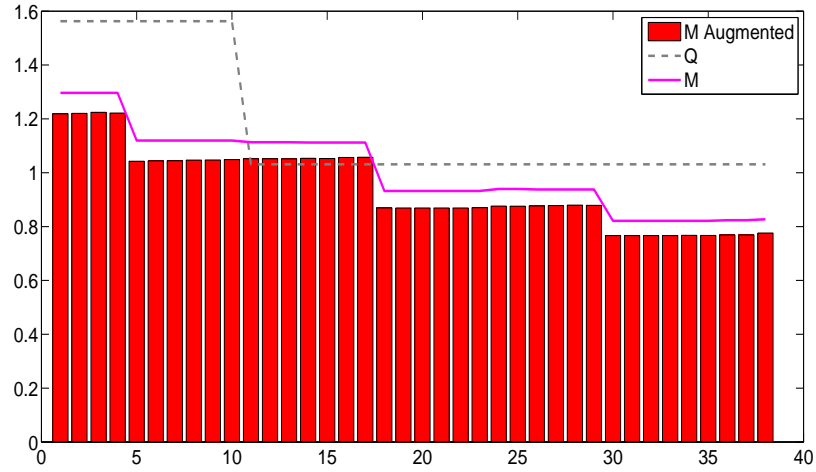


Figure 4: RMSFE of the now-cast of the output gap throughout the quarter for the quarterly model (Q, the dashed line), the monthly model (M, the purple line) and the monthly model augmented with the auxiliary information (M Augmented, the red bars).

351 The forecasts are updated 38 times throughout the quarter, corresponding
 352 to the stylized calendar B.4 described in Appendix B. We can thus associate
 353 to each update of the forecasts a date and a set of information being re-
 354 leased. We first report how the root mean square forecast error (RMSFE) of
 355 our forecasts and now-casts changes with new information releases. So the
 356 horizontal axis of the Figures 3 -4 indicate the grouping of releases corre-
 357 sponding to the calendar. For example, clusters 5, 18, and 30 correspond to
 358 the release of the employment situation in each of the three months of the
 359 quarter, release 11 corresponds to the flash estimate of GDP for the previous
 360 quarter and 14, 26 and 38 correspond to the last day of each month where
 361 we include the financial data.

362 Notice that the now-cast of the quarterly model that uses the balanced
 363 panel (Q balanced) can be updated only once in the quarter, when the GDP
 364 for the past quarter is released (cluster 10). The now-casts of the monthly
 365 model (M model) is updated 9 times throughout the quarter, at each release
 366 of the variables that are released at least monthly - consumption (12, 24, 36),
 367 the employment variables (5, 18, and 30) and the term structure variables
 368 (14, 26 and 38). The monthly model augmented by auxiliary variables (M
 369 Augmented) is updated at each new release. The number of jumps in the root
 370 mean square forecast errors (RMSFE) of each of the now-casts in Figures 3-4
 371 reflects how many times the now-cast is updated throughout the quarter.

372 Results indicate that the monthly specification is very useful especially
 373 when the focus is on a variable available at the monthly frequency such

	SPF	Q	M	M Augmented
GDP growth				
5	-	0.6557	0.5751 *	0.5754 **
20	0.4841 **	0.5662	0.5520	0.5121 *
30	-	0.5662	0.5219 *	0.4611 ***
38	-	0.5662	0.5027 ***	0.4338 ***
Unemployment				
5	-	0.2556	0.0607 ***	0.0607 ***
20	0.0190 ***	0.0587	0.0241 **	0.0253 **
30	-	0.0587	0.0066 ***	0.0065 ***
38	-	0.0587	0.0071 ***	0.0070 ***
GDP Deflator inflation				
5	-	0.0573	0.0568	0.0580
20	0.0389 *	0.0446	0.0434	0.0459
30	-	0.0446	0.0449	0.0489
38	-	0.0446	0.0482	0.0517

Table 1: **RMSFE at representative vintages for GDP growth, the unemployment rate and GDP deflation inflation now-casts.** The first column indicates the vintages. We indicate with ***, ** and * the forecasts that are statistically significantly different from the forecast produced by the model with the balanced panel (Q, second column in the tables) with a 1%, 5% and 10% level, respectively, based on the Diebold-Mariano (1995) test, where we use Newey-West standard errors to deal with the autocorrelation that multi-period forecast errors usually exhibit. The bold type face is used to identify forecasts that are statistically significantly better.

as unemployment (Table 1) and the output gap (Figure 4). Recall that the latter is defined as the difference between actual output and the output that would prevail in the flexible price and wage economy in the absence of distorting price and wage markup shocks which, in the GSW model, is very closely aligned to the total employment series, also available monthly⁷. In this case the main advantage comes from the ability to account for the

⁷Since the output gap is unobserved, we take it's ex-post estimate - *i.e.* the estimate produced by the quarterly DSGE model using all available data up to 2014Q2 - to be the "true" one, and we construct the RMSFE of the now-cast produced by the alternative models we consider with respect to it.

380 monthly observables in a more consistent way, rather than from the real-time
381 data flow.

382 For quarterly GDP, on the other hand, we can see that the best per-
383 formance is generated by the monthly model augmented by the auxiliary
384 variables (see Figure 3). The RMSFE errors decline with the arrival of new
385 information throughout the quarter confirming results obtained in reduced
386 form models as surveyed by Banbura, Giannone and Reichlin (2011). The
387 importance of the monthly data flow is confirmed by Figure 5 which reports
388 the now-cast for the GDP growth for four representative vintages produced
389 with information sets 5, 20, 30 and 38. Notice that with the monthly model
390 with the auxiliary data we would have had a much timelier assessment of the
391 depth of the Great Recession, as well as a better assessment of the recovery.

392 The results on the GDP deflator inflation are very disappointing for all
393 models. All of them, including the SPF, have a similar now-casting perfor-
394 mance the (Table 1). This is not surprising since this variable is itself flat
395 over the forecasting sample.

396 In Appendix C we perform the same evaluation for the two sub-samples,
397 1995-2007 and 2008-2014. We show that the relative forecasting performance
398 of the models is quite different before and after the Great Recession for most
399 variables and that in the second sub-sample there is a significant deterioration
400 of performances.

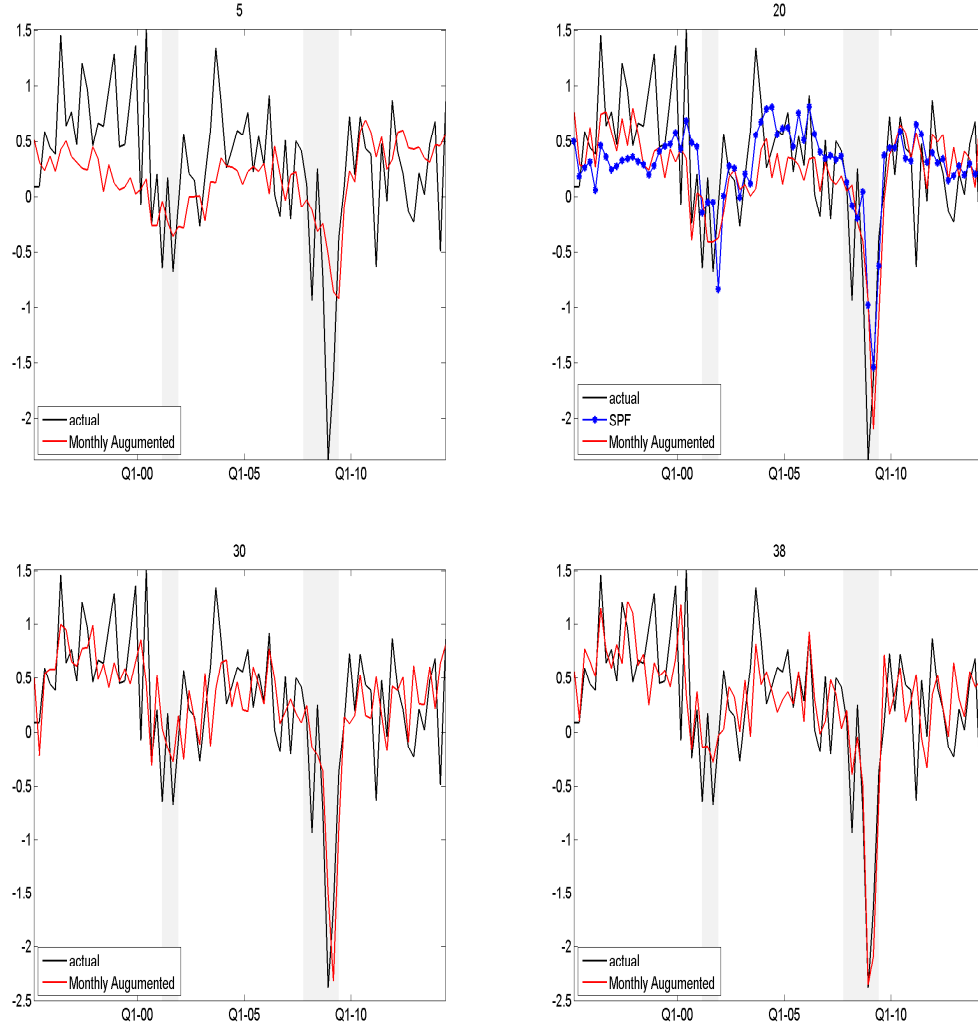


Figure 5: **The now-cast of annualised GDP growth for 4 representative vintages.** Vintage 5 corresponds to the release of the employment data on the first Friday of the first month of the quarter. Vintage 20 is the middle of the second month of the quarter and we take it to correspond to the moment at which the SPF make their forecast. Vintage 30 corresponds to the release of the Employment data at the beginning of the third month of the quarter. The lower right panel correspond to the last day of the quarter (vintage 38). The shaded area indicates the NBER recession dates.

	GDP growth and Unemployment			All real variables		
	Q	M	M Augmented	Q	M	M Augmented
5	-1.7632	-1.2326	-1.2297	-9.9931	-8.8426	-8.6282
20	-1.225	-1.0894	-1.0651	-7.8794	-7.3741	-7.1988
30	-1.225	-0.9269	-0.8523	-7.8794	-6.1578	-5.9231
38	-1.225	-0.9054	-0.7819	-7.8794	-5.4332	-4.9318

Table 2: **Log predictive score of the now-cast of unemployment and GDP growth and for all on the models' real variables at representative vintages.** The first column indicates the vintages. Vintage 5 corresponds the release of the employment data on the first Friday of the first month of the quarter. Vintage 20 is in the first half of the the second month of the quarter and we take it to correspond to the moment at which the SPF make their forecast. Vintage 30 corresponds to the relase of the Employment data at the beginning of the third month of the quarter. Vintage 38 is the last day of the quarter.

4.2. Density Forecasts

In order to characterize and evaluating the uncertainty associated with the predictions of the model we compute the predictive density of the models and the associated log predictive scores. The log predictive score is a widely used scoring rule, used to evaluate the quality of probabilistic forecasts given a set of outcomes. Formally it is defined here as:

$$S_h(\mathcal{M}) = \frac{1}{N_h} \sum_{t=T}^{T+N_h-1} \ln p(y_{t+h}|Y_{1:T-1}, \mathcal{M}), \quad (11)$$

where h is the forecast horizon, T is the beginning of the forecast horizon and $\ln p(y_{t+h}|Y_{1:T-1}, \mathcal{M})$ is the marginal likelihood for $h = 1$.

Table 2 reports the log predictive score produced after each of the 4 representative clusters of releases (5,20,30,38), respectively for the now-cast of unemployment and GDP growth and for all on the models' real variables,

412 i.e. all variables but the interest rate and the spread. In both cases the two
413 monthly models are the best performing and the M augmented is consistently
414 better than the monthly model that does not exploit the panel.

415 *4.3. Exploiting the model's structure in real-time*

416 One of the key advantages of our methodology is the ability to exploit the
417 structure of the model in real time. As we have seen, we can obtain real-time
418 estimates of unobservable variables such as the output gap and update them
419 at each information release (see Figure 4). We can also use the model and
420 the structural shocks it identifies to interpret the signal coming from the data
421 in real time.

422 The decomposition of the fluctuations in terms of structural shocks changes
423 with the data arrival in real time. Let us focus, for example, on the story be-
424 hind the drop in GDP in the last quarter of 2008Q4, when Lehman Brothers
425 collapsed. Let's now compare the ex-post decomposition reported in Figure
426 1 with that obtained in real time. We place ourselves at the beginning of
427 July 2008 and look at how each of the models would have attributed the
428 shocks according to the information flow up until March 2009 in the case of
429 the quarterly balanced model (top panel of Figure 6) and the monthly model
430 with auxiliary information (bottom panel). We also generate the same graph
431 for the quarterly model conditioned on the now-casts produced by the SPF
432 (middle panel of Figure 6). Conditioning on SPFs has been suggested by
433 Del Negro and Schorfheide (2013) as a way of indirectly exploiting timely

434 information (as preprocessed by the SPF) in the forecast. On the right side
435 of these graphs, we add the ex-post shock decomposition highlighted in red
436 in Figure 1 for ease of comparison.

437 One of the key messages emerging from the comparison of the graphs in
438 Figure 6 is that accounting for new information in a timely fashion not only
439 delivers an early signal on the state of the economy but also on its drivers.
440 In other words, it takes time to understand why the economy is slowing and,
441 in real time, there is significant uncertainty surrounding the decomposition
442 of the shocks. Exploiting high frequency information significantly decreases
443 this uncertainty: we converge a few months in advance to the ex-post decom-
444 position. This aspect of real time analysis has been completely disregarded
445 in the literature.

446 The charts also tell us that simply conditioning on the SPF, although
447 providing a forecast which is at least as accurate than that our M Augmented
448 framework, does not help in recognising in real-time the shocks that are
449 driving the fall of GDP in 2008Q4. Clearly, each of the the auxiliary variables
450 carries a meaningful signal which would have been lost by simply conditioning
451 on the view of the SPF, who pre-process the available information into a
452 single now-cast for each observable. This confirm results in Monti (2010)
453 showing that conditioning on the SPF as if they were actual data rather
454 than forecasts⁸ can be misleading.

⁸Del Negro and Schorfheide (2013) call this the *news* implementation of the condition-
ing as opposed to the *noise* implementation, in which the SPF now-casts are considered

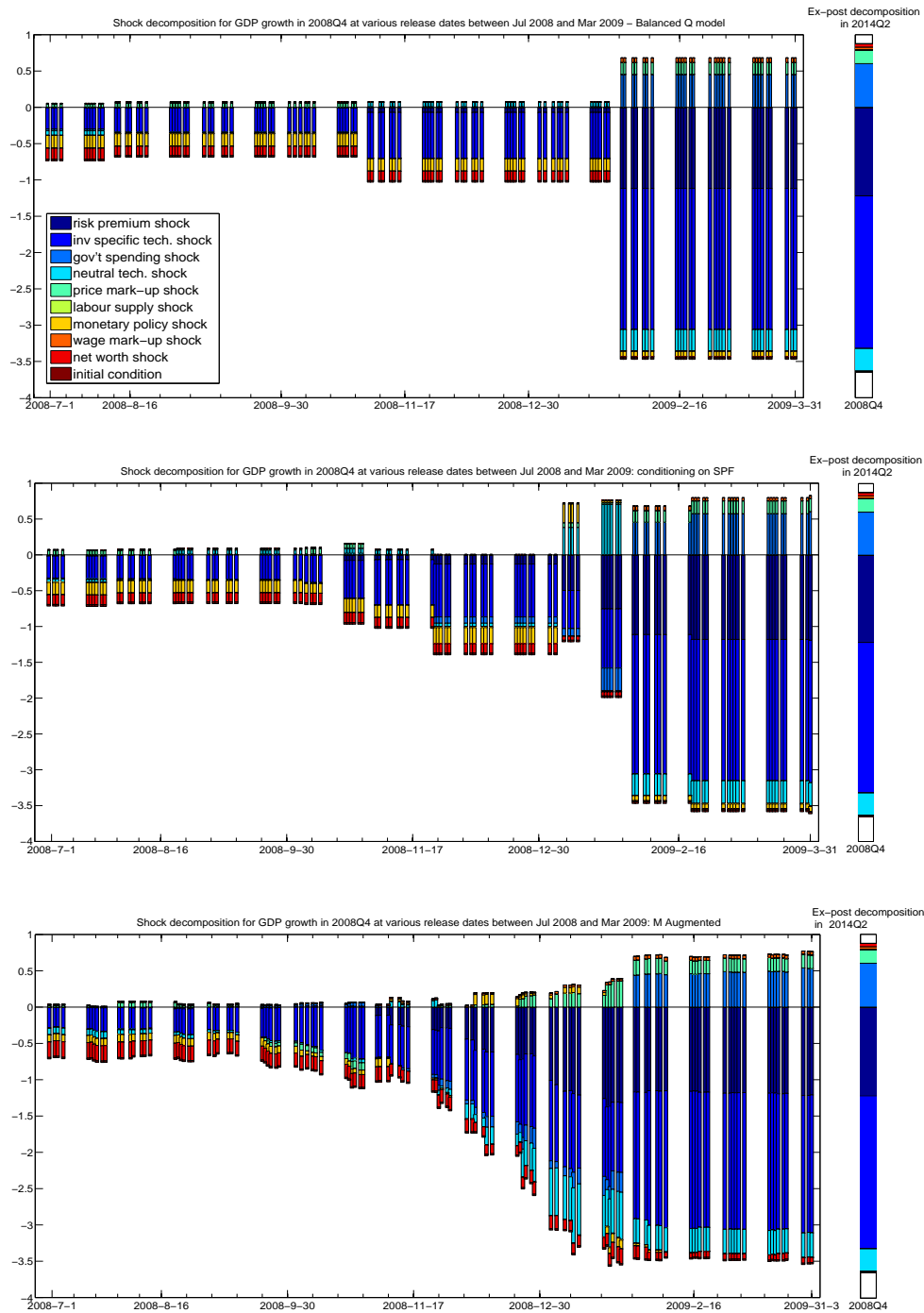


Figure 6: Shock decompositions in real tim for Q, Q+SPF and M Augmented models

455 In particular, the shocks decomposition obtained by conditioning on the
 456 SPF grossly underestimates the effect of the risk premium shock and, more
 457 importantly, almost misses the negative contribution of the neutral technol-
 458 ogy shock. The monthly model with auxiliary model identifies the negative
 459 contribution of the technology shock to the slowdown because the latters, as
 460 we have seen earlier, have a large impact on real variables, and the auxiliary
 461 variables related to those (e.g. surveys) are signaling at an early stage that
 462 there is a significant slowdown of the real economy and not only a large shock
 463 in the risk premium.

464 **5. Discussion and relation with the literature**

465 The approach proposed in this paper adds a new complementary perspec-
 466 tive to related work in this area. A natural alternative to our approach would
 467 have been to specify the DSGE model at the monthly frequency and deal with
 468 the mixed frequency problem arising from the fact that some key macro vari-
 469 ables are quarterly - like GDP and the GDP deflator - using, for example, the
 470 blocking technique described in Zamani *et al.* (2011). However, the problem
 471 with specifying the DSGE at a monthly frequency is that most DSGE mod-
 472 els are quarterly and there is very little empirical experience regarding the
 473 specification of the behavioral equations and the setting of the priors in a
 474 monthly set-up. The few papers that estimate monthly DSGE models (e.g.,

noisy measures of the true signal.

475 Hilberg and Hollmayr 2013) somewhat mechanically adjust the parameters
476 from their quarterly specification to the monthly equivalent. While this is
477 relatively straightforward, it is much less obvious that the specification of the
478 driving processes would carry through unchanged when specified at higher
479 frequency.

480 A different motivation for considering mixed frequency data in structural
481 models is to improve the estimation of the structural parameters of the quar-
482 terly DSGE by alleviating the temporal aggregation bias and mitigating iden-
483 tification issues (see Foroni and Marcellino, 2013, and Kim, 2010). In that
484 approach monthly data are used to obtain better estimates of the parameters
485 of the model. Contrary to this, and for the same reasons explained above,
486 we keep the parameters estimated via the quarterly model untouched and
487 use the data for obtaining progressively better estimates of the states, given
488 those parameter estimates. Our approach is desirable especially in policy
489 institutions where the DSGE models used for forecasting are generally very
490 complex, they might have taken several months, or even years, to agree on,
491 build and estimate and therefore require a lot of time and effort to change,
492 re-estimate, and explain anew to the policymakers. In such circumstances it
493 is unpractical and possibly unreasonable to re-estimate the model frequently.
494 This makes our framework more desirable.

495 Finally, let us comment on the aspect of our approach which combines
496 the structural model with auxiliary data. A similar idea is in Boivin and
497 Giannoni (2006) who have proposed to estimate structural DSGE model by

498 treating observable variables as imperfect measures of the economic concepts
499 of the model. In this context, they show that augmenting the model with
500 quarterly auxiliary variables can improve the identification of the states of the
501 model and hence improve the estimation of the structural parameters in the
502 quarterly model. Contrary to their approach, our emphasis is on exploiting
503 the timelines of un-modelled timely data in order to obtain early estimates
504 of modeled key variables, such as GDP growth, or latent concepts, such as
505 the output gap, and provide a structural interpretation in real time.

506 The framework proposed here builds on our early work in Giannone,
507 Monti and Reichlin (2010). In the present work we have solved an important
508 identification problem arising to time aggregation which limited the applica-
509 bility of the framework and provide a precise analytical solution which gives
510 identification conditions that can be tested in practice. We believe that this
511 solution is of more general interest than the specific application of this paper.
512 Furthermore the empirical analysis highlights a wide range of applications of
513 general use for policy and academic research which were not explored in that
514 early work.

515 **6. Conclusions**

516 The paper develops a framework to combine the insights provided by
517 structural models and the real time analysis of the flow of data publications
518 (now-cast).

519 In this framework we “borrow” the quarterly parameter estimates of the

520 DSGE and we provide a mapping from a quarterly dynamic stochastic gen-
521 eral equilibrium (DSGE) model to a monthly specification that maintains
522 the same economic restrictions and has real coefficients. We then show how
523 to adapt the monthly model so as to take into consideration realistic features
524 of the information structure such as non-synchronous infra-quarter data re-
525 leases. Finally we augment the model with data which are potentially useful
526 for providing early signals on the state of the economy but are not included
527 in the DSGE.

528 By construction, by the time quarterly data are published, the approach
529 has no advantage with respect to the standard quarterly DSGE model. How-
530 ever, at any time before that date, it allows exploiting the data flow for up-
531 dating, given the estimated parameters, the estimates of the states. This
532 delivers increasingly accurate signals about the current value of key variables
533 as well as capturing the effect of particular shocks in real time.

534 Our empirical application shows that timeliness matters for both the fore-
535 cast and its structural interpretation. It also highlights that the shock decom-
536 position is very uncertain in real time and that, by exploiting high frequency
537 information, we can significantly decrease this uncertainty with the estimates
538 of the shocks converging to the ex-post decomposition faster. Although much
539 research has been devoted to real time analysis, the identification of struc-
540 tural shocks in real time has been typically overlooked in the literature. In
541 our analysis of the great recession we have shown that our framework would
542 have allowed to understand faster than the quarterly model that the econ-

543 omy was being hit not only by a risk premium shock but also by a technology
544 shock, therefore signaling at an early stage that both the financial sector and
545 the real economy were affected.

546 Finally, let us highlight that our proposed approach is simple and not
547 invasive, as it can be applied to existing DSGEs with no need to re-estimate
548 them frequently and without changing the model's ex-post interpretation of
549 the data.

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Appendix A. The model

Here we summarize the key log-linear equations of the GSW model. We refer to Galí, Smets and Wouters (2012) for a more detailed description of the model.

- Consumption Euler equation:

$$\hat{c}_t = c_1 E_t [\hat{c}_{t+1}] + (1 - c_1) \hat{c}_{t-1} - c_2 \left(\hat{R}_t - E_t [\hat{\pi}_{t+1}] - \hat{\varepsilon}_t^b \right)$$

with $c_1 = (h/\tau)/(1 + (h/\tau))$, $c_2 = (1 - h/\tau)/(1 + (h/\tau))$ where h is the external habit parameter. $\hat{\varepsilon}_t^b$ is the exogenous AR(1) risk premium process.

- Investment Euler equation:

$$\hat{i}_t = i_1 \hat{i}_{t-1} + (1 - i_1) \hat{i}_{t+1} + i_2 \hat{Q}_t^k + \hat{\varepsilon}_t^q$$

with $i_1 = 1/(1 + \beta)$, $i_2 = i_1/(\tau^2 \Psi)$ where β is the discount factor and Ψ is the elasticity of the capital adjustment cost function. $\hat{\varepsilon}_t^q$ is the exogenous AR(1) process for the investment specific technology.

- Aggregate demand equals aggregate supply:

$$\hat{y}_t = \frac{c_*}{y_*} \hat{c}_t + \frac{i_*}{y_*} \hat{i}_t + \hat{\varepsilon}_t^g + \frac{r_*^k k_*}{y_*} \hat{u}_t \quad (\text{A.1})$$

$$= \mathcal{M}_p \left(\alpha \hat{k}_t + (1 - \alpha) \hat{L}_t + \hat{\varepsilon}_t^a \right) \quad (\text{A.2})$$

with \mathcal{M}_p reflecting the fixed costs in production which corresponds to the price markup in steady state. $\hat{\varepsilon}_t^g, \hat{\varepsilon}_t^a$ are the AR(1) processes representing exogenous demand components and the TFP process.

- Price-setting under the Calvo model with indexation:

$$\hat{\pi}_t - \gamma_p \hat{\pi}_{t-1} = \pi_1 (E_t [\hat{\pi}_{t+1}] - \gamma_p \hat{\pi}_t) - \pi_2 \mu_t^p + \hat{\varepsilon}_t^p$$

with $\pi_1 = \beta$, $\pi_2 = (1 - \theta_p \beta)(1 - \theta_p) / [\theta_p (1 + (\mathcal{M}_p - 1) \varepsilon_p)]$ and θ_p and γ_p are, respectively, the probability and indexation of the Calvo model, and ε_p is the curvature of the aggregator function. The price markup μ_t^p is equal to the inverse of the real marginal $\hat{m}c_t = (1 - \alpha) \hat{w}_t + \alpha r \hat{k}_t - \hat{A}_t$.

- Wage-setting under the Calvo model with indexation:

$$\pi_t^w = \gamma_w \pi_{t-1}^p + \beta E_t [\pi_{t+1}^w - \gamma_w \pi_t^p] - \lambda_w \phi u_t + \lambda_w \mu_t^w$$

where the unemployment rate $u_t = l_t - n_t$ is defined so as to include all the individuals who would like to be working (given current labour market conditions, and while internalizing the benefits that this will bring to their households) but are not currently employed.

- Capital accumulation equation:

$$\hat{k}_t = \kappa_1 \hat{k}_{t-1} + (1 - \kappa_1) \hat{i}_t + \kappa_2 \varepsilon_t^q$$

with $\kappa_1 = 1 - (i_*/\bar{k}_*)$, $\kappa_2 = (i_*/\bar{k}_*)(1 + \beta)\Psi$. Capital services used in production are defined as: $\hat{k}_t = \hat{u}_t + \hat{k}_{t-1}$

- Optimal capital utilisation condition:

$$\hat{u}_t = \frac{1 - \phi}{\phi} \hat{r}_t^k$$

with ϕ being the elasticity of the capital utilisation cost function.

- Optimal capital/labour input condition:

$$\hat{k}_t = \hat{w}_t - \hat{r}_t^k + \hat{L}_t$$

- Monetary policy rule:

$$\hat{R}_t = \rho_r \hat{R}_{t-1} + (1 - \rho_r)(r_\pi \hat{\pi}_t + r_y ygap_t) + r_{\Delta y} \Delta y_t + \varepsilon_t^r$$

where $ygap_t = y_t - yflex_t$ is the difference between actual output and the output in the flexible price and wage economy in absence of distorting price and wage markup shocks.

- In practice, as Del Negro, Hasegawa and Schorfheide (2014) show for the SW, adding the financial frictions to this model simply amount to replacing the equation for the value of the capital stock with the following conditions:

$$E_t [\hat{R}_t^k - \hat{R}_t] = b_t + \zeta_{sp,b}(\hat{Q}_t^k + \bar{k}_t - n_t) + \sigma_{\omega,t}$$

$$\hat{R}_t^k - \pi_t = \frac{r_*^k}{r_*^k + 1 - \delta} r_t^k + \frac{1 - \delta}{r_*^k + 1 - \delta} \hat{Q}_t^k - \hat{Q}_{t-1}^k$$

$$n_t = \zeta_{nrk}(\hat{R}_t^k - \pi_t) - \zeta_{nr}(\hat{R}_t - \pi_t) + \zeta_{nqk}(\hat{Q}_{t-1}^k + \bar{k}_{t-1}) + \zeta_{nn}n_{t-1} - \frac{zeta_{\sigma}a_{n\sigma}}{sp\sigma}\sigma\omega, t - 1,$$

which define respectively the spread, the return on capital and the evolution of the entrepreneurial net worth. Unlike Del Negro, Hasegawa and Schorfheide (2014) we estimate the parameters in this last equation directly. The measure of spreads in the observables is related to the model variables $E_t \left[\hat{R}_t^k - \hat{R}_t \right]$ as follows:

$$Spread = SP^* + 100 + E_t \left[\hat{R}_t^k - \hat{R}_t \right]$$

We calibrate the δ , $\frac{c}{g}$ and h to standard values of 0.025, 0.18 and 0.7 respectively, while we calibrate the following parameters to their mean posterior values in GSW (2012): $\beta = (0.31/100 + 1)^{-1}$, $\Psi = 3.96$, $\zeta_p = 10$, $\rho_{chi} = 0.99$, and $cgy = 0.69$.

The priors of the estimated parameters are reported below.

Prior Distribution				Prior Distribution			
	Distr.	mean	st.dev		Distr.	mean	st.dev
ν	B	0.5	0.2	γ_p	B	0.5	0.1
ρ_π	N	1.5	0.125	γ_w	B	0.5	0.1
ρ_{ygap}	N	0.12	0.01	ψ	B	0.5	0.15
$\rho_{\Delta ygap}$	N	0.12	0.01	ρ_r	B	0.75	0.10
θ_w	B	0.5	0.1	ϕ	N	2	0.5
θ_p	B	0.5	0.1	$\zeta_{n\sigma}$	N	2	0.5
τ	N	0.40	0.1	σ_χ	U	2.5	1.44
SP^*	N	2	0.5	Π^*	G	0.62	0.1
l^*	N	0	0.1	ζ_{spb}	B	0.2	0.1
ζ_{rk}	N	0.2	0.1	ζ_{nr}	N	0.2	0.1
ζ_{nq}	N	0.2	0.1	ζ_{nn}	B	0.8	0.1
ρ_b	B	0.5	0.2	σ_b	U	2.5	1.44
ρ_q	B	0.5	0.2	σ_q	U	2.5	1.44
ρ_g	B	0.5	0.2	σ_g	U	2.5	1.44
ρ_a	B	0.5	0.2	σ_a	U	2.5	1.44
ρ_{ms}	B	0.5	0.2	σ_r	U	2.5	1.44
ρ_p	B	0.5	0.2	σ_p	U	2.5	1.44
ρ_w	B	0.5	0.2	σ_w	U	2.5	1.44
ρ_{nw}	B	0.5	0.2	σ_{nw}	U	2.5	1.44

Table A.3: Prior distribution of the parameters of the model

Appendix B. Auxiliary data and Calendar

	timing	release	publ. lag	transformation	FRED
1	1 st day of the 1 st month	-	-	-	-
2	1 st bus. day of the 1 st month	Economic Policy Uncertainty Index	m-1	1	USEPUINDXM
3	1 st bus. day of the 1 st month	PMI	m-1	1	NAPM
4	1 st bus. day of the 1 st month	construction	m-2	1	TTLCONS-
5	1 st Friday of the 1 st month	Employment situation	m-1	2 (earnings)	AWHNONAG, CE16OV, UNRATE
6	Middle of the 1 st month	CPI and PPI	m-1	2	CPIAUSL
7	15 th to 17 th of the 1 st month	Industrial Production	m-1	2	INDPRO
8	3 rd week of the 1 st month	Credit and M2 (H8 release)	m-1	2	LOANS, M2
9	later part of the 1 st month	housing starts	m-1	1	HOUST
10	3 rd Thursday of the 1 st month	Business Outlook Survey: Phil. Fed	m	1	-
11	Last week of 1 st month	GDP release	q-1		COMPNFB, FPI, GDPC1, GDPDEF
12	Day after GDP release	PCE, RDPI	m-1	2	PCE, DSPIC96
13	Day after GDP release	PCE price index	m-1	2	PCEPI
14	Last day of the 1 st month	Fed Funds rate and credit spread	m	3	FEDFUNDS, BAAY10
15	1 st bus. day of the 2 nd month	Economic Policy Uncertainty Index	m-1	1	USEPUINDXM
16	1 st bus. day of the 2 nd month	PMI	m-1	1	NAPM
17	1 st bus. day of the 2 nd month	construction	m-2	1	TTLCONS
18	1 st Friday of the 2 nd month	Employment situation	m-1	2 (earnings)	AWHNONAG, CE16OV, UNRATE
19	Middle of the 2 nd month	CPI and PPI	m-1	2	CPIAUSL
20	15 th to 17 th of the 2 nd month	Industrial Production	m-1	2	INDPRO
21	3 rd week of the 2 nd month	Credit and M2 (H8 release)	m-1	2	LOANS, M2
22	later part of the 2 nd month	housing starts	m-1	1	HOUST
23	3 rd Thursday of the 2 nd month	Business Outlook Survey: Phil. Fed	m	1	-
24	Last week of 2 nd month	PCE, RDPI	m-1	2	DSPIC96, PCE
25	Last week of 2 nd month	PCE price index	m-1	2	PCEPI
26	Last day of the 2 nd month	Fed Funds rate and credit spread	m	3	FEDFUNDS, BAA10Y
27	1 st bus. day of the 3 rd month	Economic Policy Uncertainty Index	m-1	1	USEPUINDXM
28	1 st bus. day of the 3 rd month	PMI	m-1	1	NAPM
29	1 st bus. day of the 3 rd month	construction	m-2	1	TTLCONS
30	1 st Friday of the 3 rd month	Employment situation	m-1	2 (earnings)	AWHNONAG, CE16OV, UNRATE
31	Middle of the 3 rd month	CPI and PPI	m-1	2	CPIAUSL
32	15 th to 17 th of the 3 rd month	Industrial Production	m-1	2	INDPRO
33	3 rd week of the 3 rd month	Credit and M2 (H8 release)	m-1	2	LOANS, M2
34	later part of the 3 rd month	housing starts	m-1	1	HOUST
35	3 rd Thursday of the 3 rd month	Business Outlook Survey: Phil. Fed	m	1	-
36	Last week of 3 rd month	PCE, RDPI	m-1	2	PCE, DSPI96C
37	Last week of 3 rd month	PCE price index	m-1	2	PCEPI
38	Last day of the 3 rd month	Fed Funds rate and credit spread	m	3	FEDFUNDS, BAAY10

Table B.4: Data releases are indicated in rows. Column 1 indicates the progressive number associated to each "vintage". Column 2 indicates the official dates of the publication. Column 3 indicates the releases. Column 4 indicates the publishing lag: e.g. IP is release with 1-month delay (m-1). Column 4 indicate the transformation: 1 indicates monthly differences, 2 indicates monthly growth rates, 3 stands for no transformation. All data are available from the FRED database of the St. Louis Fed

Appendix C. Additional Figures and Tables

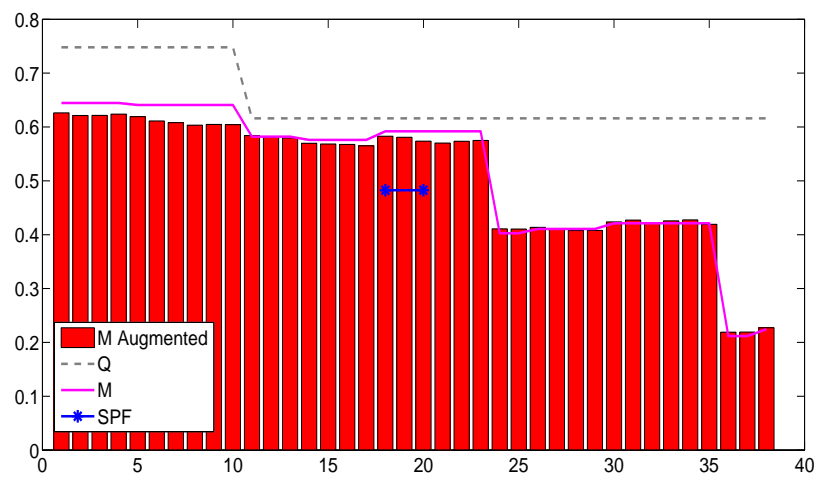


Figure C.7: **RMSFE of Consumption growth now-casts: full sample**

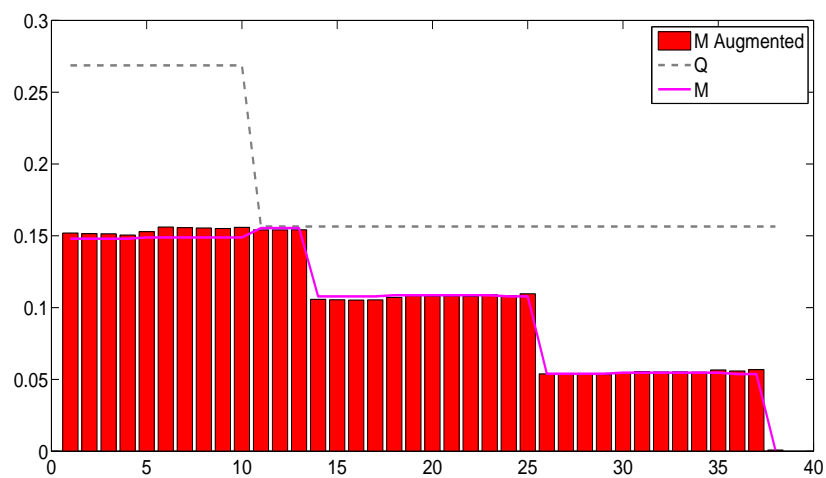


Figure C.8: **RMSFE of policy rate now-casts: full sample**

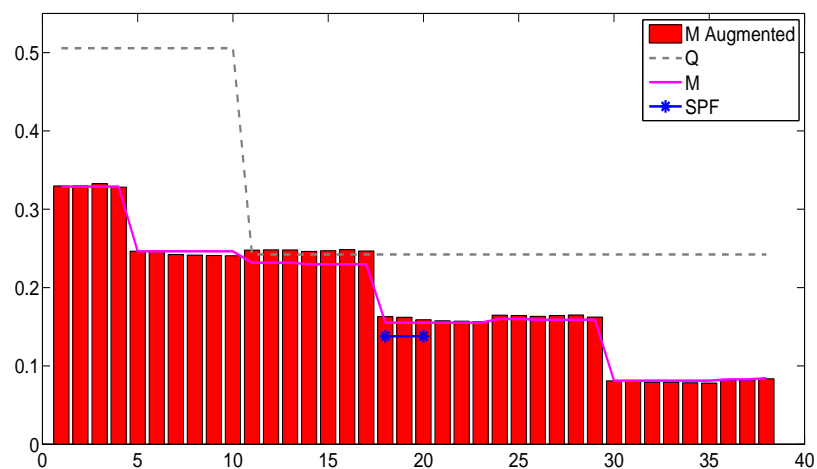


Figure C.9: **RMSFE of unemployment, estimated in real time throughout the quarter**

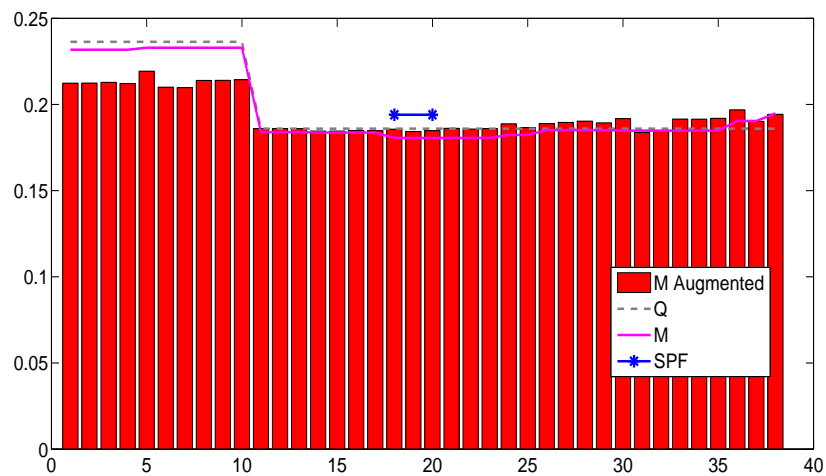


Figure C.10: **RMSFE of annual GDP deflator inflation now-casts throughout the quarter**

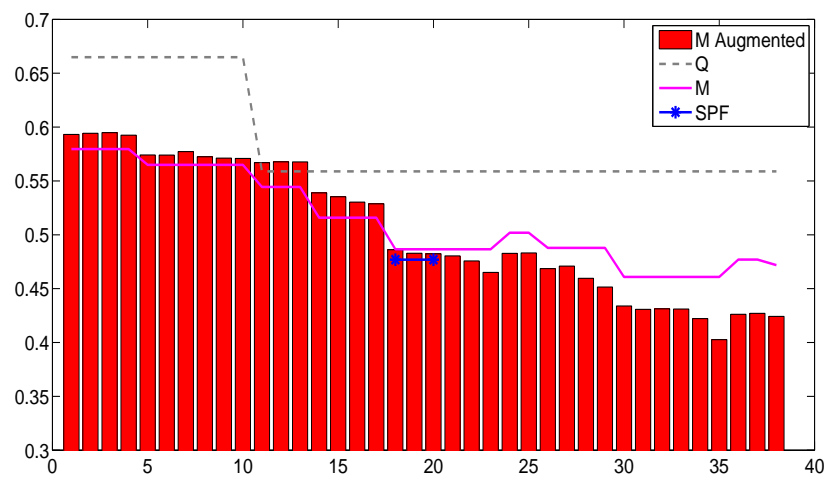


Figure C.11: RMSFE of GDP growth now-casts: 1995-2007

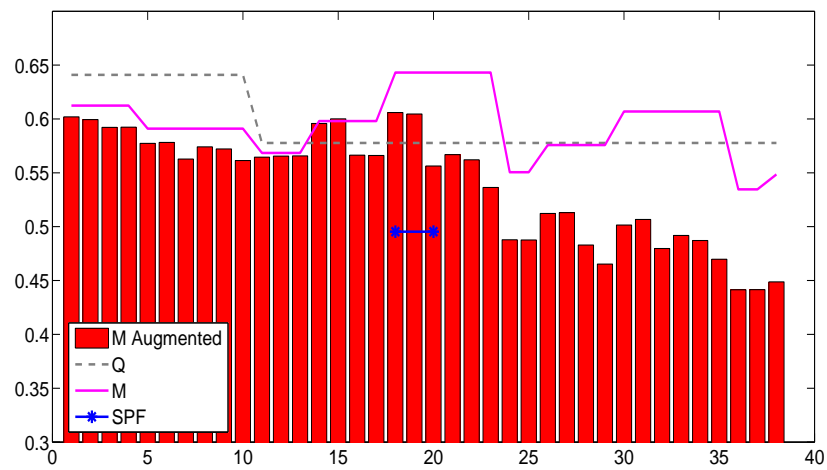


Figure C.12: RMSFE of GDP growth now-casts: 2008-2014

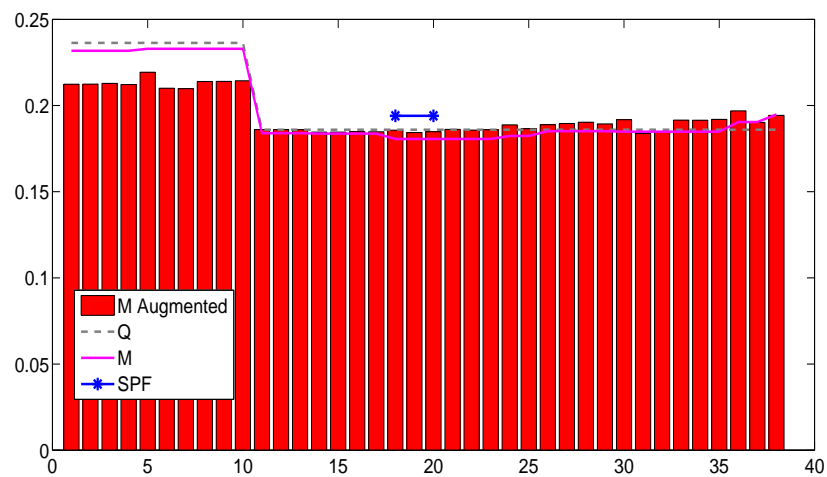


Figure C.13: RMSFE of GDP deflator inflation now-casts: 1995-2007

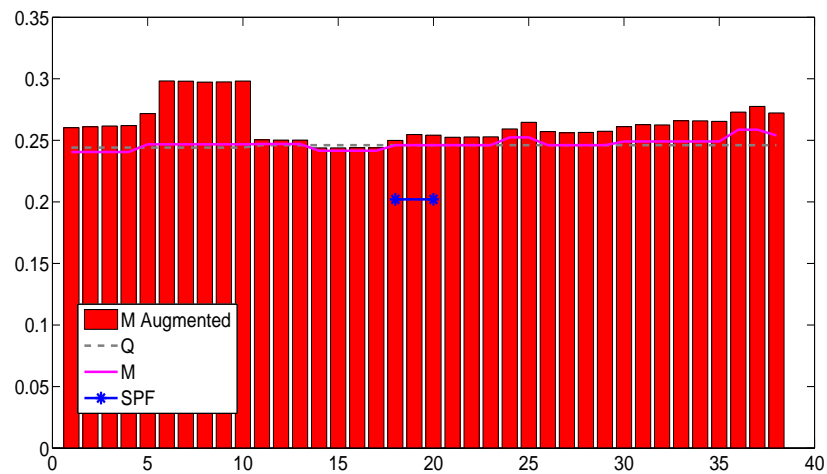


Figure C.14: RMSFE of GDP deflator inflation now-casts: 2008-2014

Table C.5: quarter-on-quarter GDP growth forecasts: pre-crisis sample -1995-2007

	SPF	Q	Q+cond	M	M+panel
Q0	0.4769***	0.5589	0.5598	0.4865*	0.4824*
Q1	0.5407**	0.6698	0.6683	0.6386	0.6526
Q2	0.5557	0.7117	0.7122	0.6878	0.7031
Q3	0.5493*	0.7091	0.7119	0.6930	0.7054
Q4	0.5613	0.6873	0.6915	0.6737	0.6877

Table C.6: annual GDP deflator inflation: pre-crisis sample - 1995-2007

	SPF	Q	Q+cond	M	M+panel
Q0	0.1940*	0.1861	0.1865 8	0.1804	0.1844
Q1	0.3754	0.3805	0.3799	0.3680	0.3737
Q2	0.5549**	0.6026	0.7064**	0.5796*	0.5824*
Q3	0.7547**	0.8517	0.8519	0.8204	0.8173*
Q4	0.9949	0.9926	0.9932	0.8669*	0.9544

Table C.7: quarter-on-quarter GDP growth forecasts: 2008-2014 sample

	SPF	Q	Q+cond	M	M+panel
Q0	0.4954***	0.5777	0.5776	0.6431	0.5563
Q1	0.6632	0.6696	0.6719	0.6593	0.6549
Q2	0.7753**	0.7260	0.7237	0.7289	0.7240
Q3	0.8553*	0.7783	0.7744	0.7902	0.7902
Q4	0.8914	0.8548	0.8552	0.8757	0.8670

Table C.8: annual GDP deflator inflation forecasts: 2008-2014 sample

	SPF	Q	Q+cond	M	M+panel
Q0	0.2020**	0.2460	0.2454	0.2461	0.2547
Q1	0.3131***	0.4104	0.4073	0.4091	0.4233
Q2	0.4663**	0.5882	0.5533	0.5821	0.5866
Q3	0.6211**	0.7696	0.7610	0.7568	0.7605
Q4	1.0191**	0.8197	0.8071	0.8137	0.7853*

RMSFE of forecasts with horizons 0 to 4, produced in the first half of the second month of the quarter (information cluster 19), approximately when the SPF produce their own forecasts. We indicate with ***, ** and * the forecasts that are statistically significantly different from the forecast produced by the model with the balanced panel (Q, third column in the tables) with a 1%, 5% and 10% level, respectively, based on the Diebold-Mariano (1995) test